sensors

Article

Case study: Spiking neural network hardware system for structural health monitoring

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Abstract: This case study provides feasibility analysis of adapting Spiking Neural Networks (SNN) based Structural Health Monitoring (SHM) system to explore low-cost solution for inspection of structural health of damaged buildings which survived after natural disaster i.e., earthquakes or similar activities. Various techniques are used to detect the structural health status of a building for performance benchmarking, including different feature extraction methods and classification techniques (e.g. SNN, K-means and artificial neural network etc.). The SNN is utilized to process the sensory data generated from full-scale seven-story reinforced concrete building to verify the classification performances. Results show that the proposed SNN hardware has high classification accuracy, reliability, longevity, and low hardware area overhead.

Keywords: Structural Health Monitoring; Damage State Classification; Spiking Neural Networks; Feature Extraction; Artificial Neural Networks

1. Introduction

Earthquake is an oscillatory movement caused by abrupt release of strain energy stored in in the rocks within the crust of earth surface. Natural disasters are always vulnerable which leads to extreme damages in nearby population in terms of fatality, communication and infrastructure loss. Flood, earthquake, cyclones etc. are among most common occurring natural disasters across world. The impact of these disasters differs in geological and geographic location of an area. These disasters come with no advance warning but an effective, well prepared and maintained infrastructure will decrease potential impact of future disasters. The structural health of buildings and other infrastructures suffers degradation due to environmental catastrophes caused by ageing, hazards and natural disasters [1]. In any area, public infrastructures like school, hospital, fire station, administrative buildings, bridges, treatment plants are more prone to be highly affected by these disasters. Therefore, regular structural health monitoring is required to ensure heath and endurance from these mega structures. In an event of disaster, it is particularly important i). to detect and quantify the severity of damage caused by environmental disasters at an early stage, ii). to assess the current structural health and reliability of buildings to ensure its safe use, and iii) to estimate repairing cost for damage to minimize economic losses [2]. Traditional monitoring methods rely on an inspection and assessment of the buildings and requires experienced inspectors. Many structures are not convenient for on-site monitoring due to the terrain obstacles i.e., lack of access to such buildings and which sometimes makes it too late due to the retrospective nature of inspections [3]. An automated process such as installation of a Structural Health Monitoring (SHM) system on vulnerable structures, e.g. buildings, bridges and even special launch vehicles, to periodically detect and notify structural damages [4]. An advance SHM systems should include current health profile of the structure, the functions of damage detection, structural life prediction etc. [5]. The lifespan of typical structure lasts for decades whereas sensory instruments and microprocessors used by SHM systems comes with limited lifespan, e.g. in an ideal operating environment the three-axis accelerometer of IIS3DHHC from the STMicroelectronics has ten-year production life which further shrinks in harsh outdoor environments. Therefore, after installation and regular use for several years SHM systems may fatigue and fail. Due to technical and economic difficulties for secondary deployment, the longevity and reliability of SHM systems are key challenges that must be considered.

Considering these issues, SHM Systems should offer three characteristics. Firstly, the system should be adaptive, robust, and capable to learn quickly. Secondly, the data analysis of the SHM system should be fast, efficient and accurate. Finally, the longevity and reliability of the systems hardware should be enhanced as the SHM system may be deployed in harsh conditions. The SHM system must has protection capabilities to resist the hazardous effect of external environment. Recent research suggested that we can build human brain like fault-tolerant energy-efficient system with learning capability to enhance the robustness, productivity and endurance of the electronic hardware systems [6,7]. Spiking neural network (SNN) are referred as the 3rd generation of artificial neural network (ANN). Contrary to conventional ANNs, SNNs are more realistic mathematical representation of the human brain that mimics biological spike-based event-driven processes to communicate between neurons. SNNs are computationally complex and powerful than conventional ANNs [8]. On an embedded processor, this digital systems like spike-driven communication capability makes SNNs i.e., astrocyte-neural network model more energy-efficient and reliable than deep neural network [9]. Therefore, this paper proposes an SHM system that based on SNN hardware to address the challenges of longevity and reliability of the monitoring system. The acceleration data collected from a full-scale seven-story reinforced concrete building are analyzed and severity of damage in the building are subsequently classified. The proposed system can monitor and detect the structure health damage levels under different environmental conditions, and provides a high detection accuracy and relatively low hardware overhead for implementation.

The following section (section 2) explores related works and briefly reviews current SHM solutions and methodologies used to assess the structural health of buildings and structures. Section 3 defines the proposed SHM system, discusses feature analysis and classification methods for the sensor data. Section 4 provides the experimental results to demonstrate the feasibility and accuracy of the proposed system through actual building sensor data. Finally, section 5 concludes the paper and gives the directions for future work.

2. Related works

SHM systems need to provide a framework for the damage classification using a continuous record of structural health monitoring data. This classification framework requires categorization of many datasets relating to different states of structural health [10]. Damage identification in SHM involves four main steps: signal acquisition, signal processing, feature extraction and classification. The acquired data are then analyzed by signal processing techniques to extract, identify and classify key features which are used for assessing the health condition of the structure. Feature extraction and classification techniques are very critical for assessment of the structural health condition in an automated system. Feature extraction method focuses on extracting features which may indicate damage state 'hidden' in recorded sensor data, e.g. the orthogonal decomposition method is used for feature extraction and analysis [11]. Feature extraction relies on empirical data. As the structure is affected by the environmental conditions, sensor data includes noises which affects damage level assessment [12]. Therefore, feature extraction is a foremost and critical step for the SHM system.

Another challenge of SHM systems is the damage classification method. Previous research work proposed various damage classification methods for different structures. Conventional classification methods include clustering algorithms [13] i.e., k-means (KM) which is widely used in SHM. However, KM is sensitive to the extracted data features and the initial choice of cluster centres [14] that may lead to erroneous classifications [13]. ANNs has shown to be a promising technique for SHM classification [9]. It includes a set of computational models inspired by the interconnected neurological structure of the human brain for learning and solving problems such as pattern recognitions. Taking into account the different classification rules of different structures and the use of different types of sensors [15] (e.g. sensors for measuring mechanical properties [16,17] and sensors for measuring environmental properties [18–20]), neural networks have the ability to extract features from the data automatically [21], which can meet the requirements of applications. However, existing systems are not suitable for detecting and analysing the structural characteristics in real applications such as SHM, as the system cannot meet practical needs in terms of hardware cost and power consumption.

Unlike traditional ANN, Spiking Neural Networks (SNNs) have a smaller hardware overhead and are more reliable and power efficient. It has been reported that SNN hardware such as neuromorphic systems consume two orders of magnitude less energy than ANNs [22]. In brain-inspired intelligence research, SNNs demonstrate a low power consumption and high performance for the deployment of artificial intelligence technology. In addition, if considering the glial cell such as astrocyte, spiking neural astrocyte networks have shown the self-repairing capability by using a novel learning rule [23]. Therefore, this work proposed an SHM solution based on SNN hardware system with self-repairing capability that will improves the electronic system reliability and life-span in harsh environments. To the best of the authors' knowledge, conventional ANN and Probabilistic Neural Networks (PNN) are widely used for structural damage detection [24–26], but no structural health monitoring application of SNN has been reported in the literature. Therefore, by combining the energy-efficient SNN classification algorithm and the highly compact neural network hardware, the performance and lifetime of the SHM system can be improved. Results in section 4 will demonstrate the proposed work makes SHM a viable option with low energy consumption, anti-noise capability, and an efficient data processing capability.

3. SHM system based on SNN

This section explores architectural components of proposed SNN based SHM system including data acquisition (sensors) and decision-making mechanism (damage level classification). Furthermore, benchmarks of K-means and ANN algorithms are also briefly introduced in this section.

3.1. System architecture

SHM is a multi-layered hardware system that comprises up of multiple sensors for data acquisition, communication and processing architecture to assess health of structural integrity. Figure 1 shows the structure of the proposed SHM system. System is equipped with Wired or wireless sensors such as accelerometers to collect the data from under observation structure. Through the analysis of the raw data, appropriate features can be selected and extracted from the time domain or frequency domain. After feature extraction, the data is fed into the SNN hardware system for the structure damage level assessment. The SNN encodes the pre-processed data into input spiking signals. This work proposed two SNN models to explore an efficient and cost-effective solution for SHM system. A fully connected SNN network based on Leaky Integrate and Fire (LIF) neurons with SpikeProp as learning algorithm for feature classification. Second model is based on Neucube framework [27] using the Spike Timing Dependent Plasticity (STDP) rule for the unsupervised training and deSNN [28] algorithm for supervised learning. Both models can classify the level of structure damage to identify structural health status.

SNNs use time as an input dimension and records valuable information in a spatial domain. The information received by the spiking neuron is a pulsed time series, so the analogue sensory data needs to be encoded into spatial dimension for input to the spiking neural network. spiking neuron membrane changes upon arrival of input spike and each postsynaptic neuron fires an action potential or spike at the time when the membrane potential exceeds the firing threshold [29]. The event-driven neurons in an SNN are only active when they receive or emit spikes, which can contribute to energy efficiency over time.

Hardware systems that implement neuronal and synaptic computations through spike-driven communication may enable energy-efficient machine intelligence [30]. Compared with the traditional neuron model, the spiking neuron model has lower power consumption and is also suitable for parallel computing. Therefore, using a spiking neural hardware system can speed up the computation power.

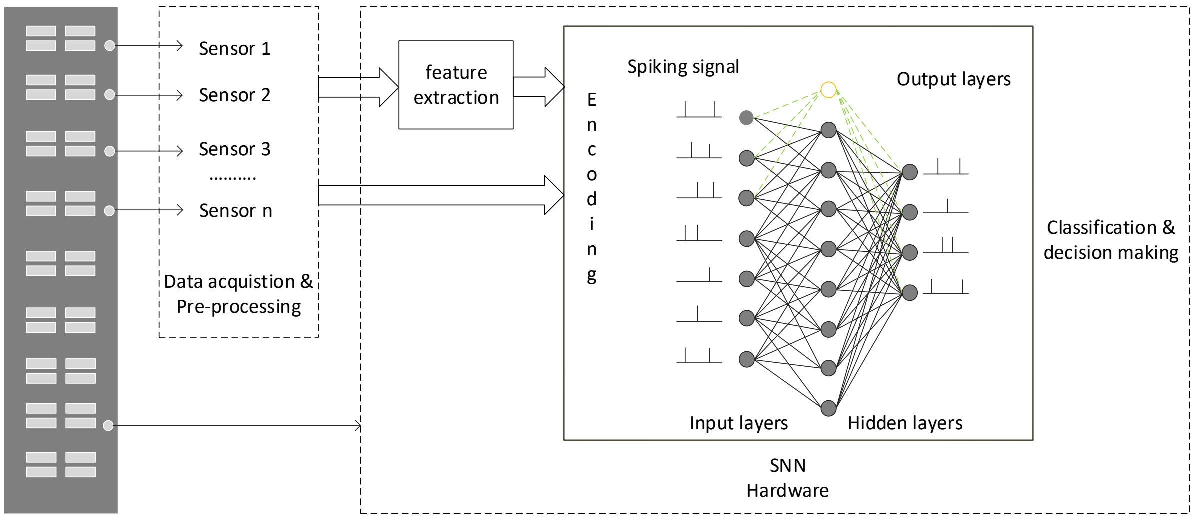


Figure 1. An SNN-based SHM system

3.2. Feature extraction

Considering different sensors used in the structure, the selection of damage-sensitive features is generally based on multiple tests, so as to determine which features can indicate the health state of the structure accurately and are robust to the influence of the structural conditions and environments. These features can be extracted from the time domain (e.g. mean, variance, peak to peak amplitude, Zero crossing rate, energy, maximum amplitude, etc.), and frequency domain such as Fourier transform. Mean, variance and zero crossing rate are defined as:

$$mean(a) = \frac{1}{N}\sum_{i=1}^{N} a_i \tag{1}$$

$$variance(a) = \frac{1}{N}\sum_{i=1}^{N}(a_i - mean(a))^2 \tag{2}$$

$$zcr(a) = \frac{1}{N-1}\sum_{i=1}^{N-1} \Pi\{a_i a_{i-1} < 0\}, \Pi\{A\} = \begin{cases} 1 & A\ is\ true \\ 0 & A\ is\ faulse \end{cases} \tag{3}$$

where a is the input sensor data, N is the number of the samples. After feature extraction, supervised or unsupervised learning methods can be used for data analysis and structure health status classification.

3.3. Structure damage classification

Temporal coding schemes such as Address event representation (AER), Bens spike algorithm (BSA) and step forward (SF) are used to represent information as an input to SNNs. Figure 2 shows different encoding results for the same temporal input data. The spike trains will carry key information of the original signals. Different spike encoding algorithms have distinct characteristics when representing input data. BSA, shown in Figure 2 (c), is suitable for high frequency signals, so there are few spikes encode from the low frequency signals, while AER and SF are better to represent the signal intensity.

Different spiking neuron models can be used to model spike generations at different description levels of biology [9], such as leaky integrate-and-fire (LIF), Izhikevich and Hodgkin–Huxley. The LIF neuron is one of the simplified models, which can be modelled as:

$$\tau_{\mathrm{m}} \frac{dV_{mem}}{dt} = -\left(V_{mem} - V_{eq}\right) + RI^{ext} \tag{4}$$

where V_{mem} is the membrane potential of the neuron, I^{ext} is the external driving current, τ_{m} is the membrane time constant, R is the input resistance, and V_{eq} is the equilibrium potential of the leakage conductance.

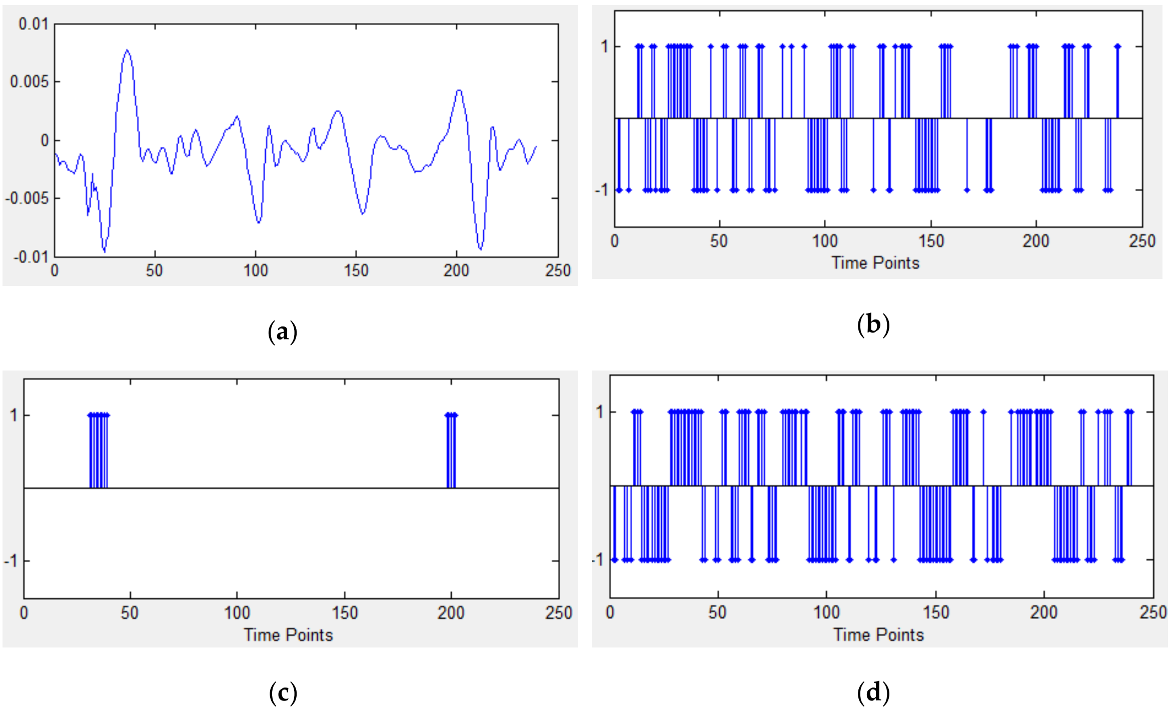


Figure 2. Spike trains generated by three different coding schemes. (**a**) Data stream of a channel; (**b**) Encoding with AER; (**c**) Encoding with BSA; (**d**) Encoding with SF. Note that spikes in (**b**), (**d**) are positive or negative, but there are only positive spikes in (**c**).

Figure 3 shows the state of the neuron updated by the membrane potential under the synaptic stimuli. When the membrane potential of the neuron crosses the threshold, the neuron then generates an output spike, which acts as an input stimulus for subsequent layer neurons.

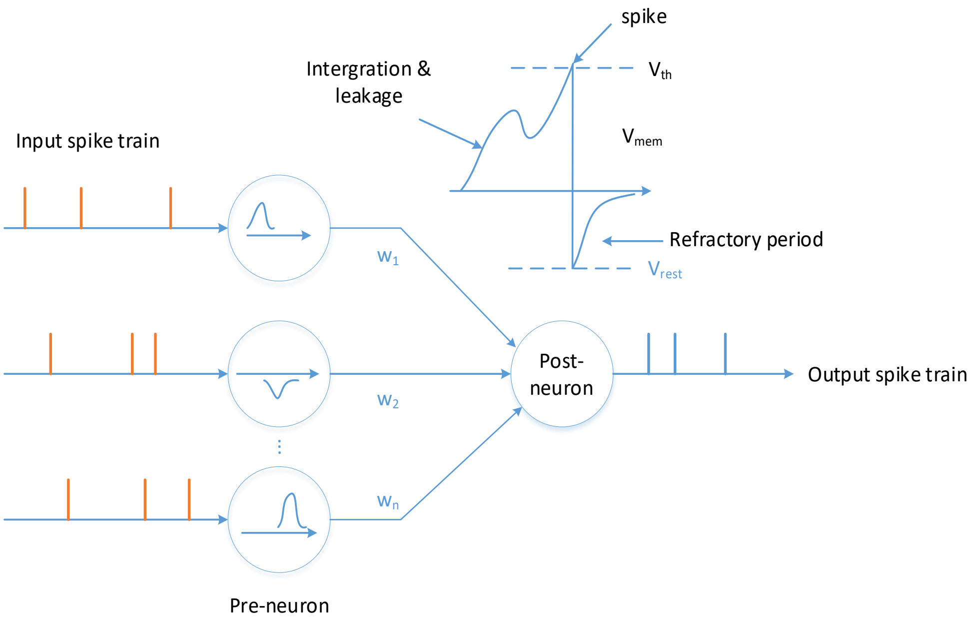


Figure 3. SNN neuron and computation model

SNN can be trained using unsupervised and supervised approaches. An unsupervised SNN using the Spike Timing Dependent Plasticity (STDP) learning rule was demonstrated with a competitive accuracy [31]. The weight update in STDP learning rule [32] can be described as:

$$\Delta w = \begin{cases} \alpha_+ e^{-\Delta t/\tau_+} & \Delta t \geq 0 \\ \alpha_- e^{\Delta t/\tau_-} & \Delta t < 0 \end{cases} \tag{5}$$

where Δw is the weight change rate, τ_+ and τ_- are STDP time constants, $\alpha_+(>0)$ and $\alpha_-(<0)$ are constant coefficients, and Δt is the time difference between a post-neuron and a pre-neuron spike. When $\Delta t \geq 0$, the synaptic plasticity is a long-term potentiation (LTP) process; otherwise it's a long-term depression process. Two different SNN structures are adopted in this study, where one is a fully connected SNN, and the other one is a model based on NeuCube [27].

For performance comparisons, commonly used classification algorithms of K-means and ANNs are also used in this work for benchmarking. A supervised learning algorithm of ANN is used in this work, where the network weights are adjusted in every iteration by comparing difference between actual output and the targeted output. A multi-layer feedforward architecture with input layer for sensory input, hidden layer for learning and an output layer to generate spiking output. The number of input neurons equals to the number of sensors whereas output layer neurons represent number of structure level classifiers. For K-means, the unsupervised K-means algorithm for SHM can be described with the following steps where k is the number of desired clusters: (a). Given features' matrix as input, find the k centroids (random or select); (b). Calculate the distances between features' vectors and centroids; (c). Group the features' vectors based on their intra-cluster distance; and (d). Iterate the algorithm and update the centroids for a better clustering result.

4. Experiments

This section explains experimental setup to generate damage level report for SHM system. Furthermore, this case study analyses and compares results of three classification methods, K-means, ANN and SNN to identify best performing SHM system.

4.1. Dataset

This case study used a full-scale seven-story reinforced concrete building dataset for experimentation [1]. The building is installed with 45 accelerometers operating at sampling rate of

240Hz. A sequence of dynamic tests was applied to the building in several months, including ambient vibration tests, free vibration tests, and forced vibration tests using the UCSD-NEES shake table. A 0.03g root-mean-square (RMS) acceleration white noise base excitation and an ambient vibration tests were performed on the structure before and between earthquake shake-table tests. For 45 channels, signal to noise ratios (SNR) are -36.97db~22.81db. The building was damaged progressively through several historical earthquake ground motions, and damage states of the building can be described as shown in Table 1. In 1st to 3rd earthquakes, the roof drift ratio, defined as the ratio between the maximum lateral displacement at the roof level of the building and the height of the roof relative to the base of the building, was measured as 0.28, 0.75 and 0.83%, respectively. The maximum tensile strain in the longitudinal reinforcing steel was measured close to the base of the wall as 0.61, 1.73 and 1.78%, respectively [1].

Table 1. Dynamic tests used in this study

Damage state	Description
State-0	8 min white noise base excitation process & 3 min ambient vibration
State-1	After the 1st earthquake excitation, with 8 min white noise base excitation process & 3 min ambient vibration
State-2	After the 2nd earthquake excitation, with 8 min white noise base excitation process & 3 min ambient vibration
State-3	After the 3rd earthquake excitation, with 8 min white noise base excitation process & 3 min ambient vibration

4.2. Feature extraction

The raw data collected from 45 channels in the building at different health states are shown in Figure 4. Raw accelerometer data of different structure states show different features, such as maximum amplitude and mean value etc. By considering the building physical movements in different states [33], the deformation degree of buildings can result in large differences in the mean and fluctuation range of accelerometer data. Based on these analysis, zero-crossing rate, mean and variance are used for feature extractions.

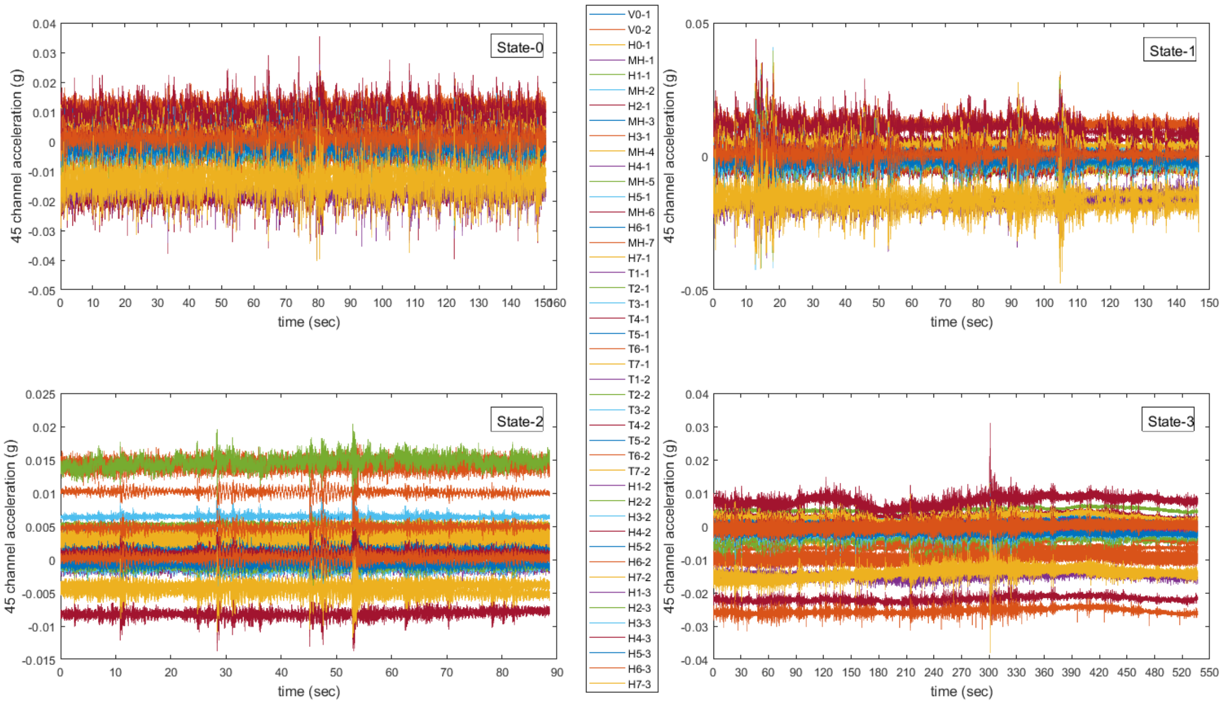


Figure 4. Row data from 45-channel accelerometers

After the data has been pre-processed, three methods (including zero-crossing rate, variance and mean value) are used to extract data in order to select the damage-sensitive features. The features are presented in Figure 5. The zero-crossing rate, which is the rate of sign-changes along a signal, is weak to separate the different damage states (indicated by colors). Among them, calculating mean value of sensor data has the potential to differentiate the four damage states.

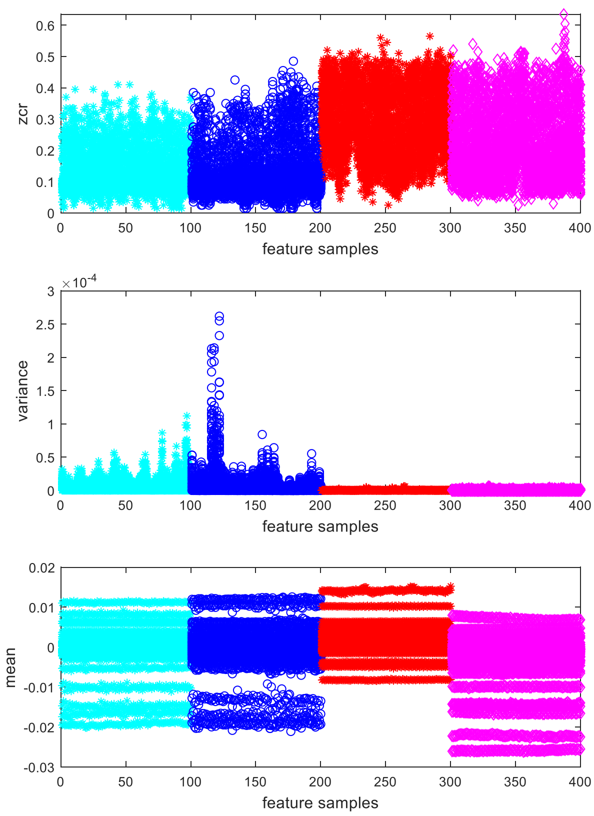


Figure 5. Results of the features extracted from raw data

4.3. SHM classification results

For different classification methods, 70%~80% samples (including mean samples and raw data) are used for training, and the rest for validation and testing.

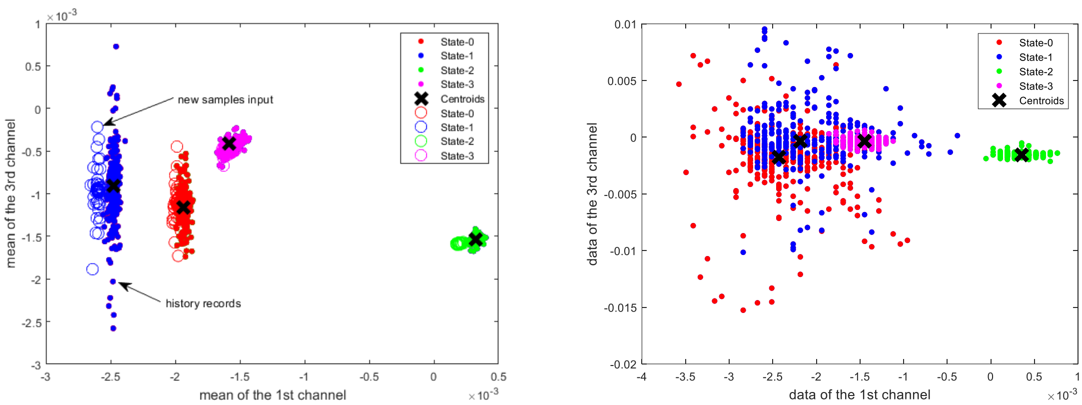
4.3.1. K-means

A 50 step-length sliding window with 100 sample points is used to get more mean samples, which are used as input for the k-means algorithm. K-means parameters are shown in table 2.

Table 2. Parameters in k-means

Parameters setting	Cluster number	Distance	Initial centroid positions	Replicates
	4	L1 distance	Random	8

It can be seen from Figure 6 (a) that using the mean value of the data as an input of the k-means algorithm can classify the health status of the building. The dots represent historical records and the circles represent new data inputs. The classification accuracy of structural health status is 100%. In Figure 6 (b), the raw data are used directly as the input of the k-means algorithm. In the case of overlapped data, including State-0, State-1 and State-3, the k-means algorithm cannot separate these data. There are 45 channels in total and only two of them are used for the demonstration in Figure 6.



(**a**) (**b**)

Figure 6. SHM classification using K-means. (**a**) Clustering of mean samples; (**b**) Clustering of raw data.

By incorporating hardware design process [34] to implement K-means, the input data dimension area will be about 3.46 **mm**^{2} and 1.23 **mm**^{2} for parallel mode and multiplexed architecture respectively.

4.3.2. ANN

The ANN with 45 input neurons, 20 hidden neurons and 4 output neurons can get similar accuracy with different input samples (mean samples and raw data). Table 3 shows that ANN slightly confuse between State-0 and State-1 when trained on raw data samples. The hardware area of the neuron is estimated about 1.347 **mm**^{2} based on a 45nm CMOS technology [35]. It can also be calculated from [36] that the total hardware area of ANN is >0.798 **mm**^{2}.

Table 3. Classification matching matrix with different input samples

(**a**) Mean samples

True label / Predict label	**State-0**	**State-1**	**State-2**	**State-3**
State-0	100%	0.0%	0.0%	0.0%
State-1	0.0%	100%	0.0%	0.0%
State-2	0.0%	0.0%	100%	0.0%
State-3	0.0%	0.0%	0.0%	100%

(**b**) Raw data

True label / Predict label	**State-0**	**State-1**	**State-2**	**State-3**
State-0	99.7%	0.3%	0.0%	0.0%
State-1	0.9%	99.1%	0.0%	0.0%
State-2	0.0%	0.0%	100%	0.0%
State-3	0.0%	0.0%	0.0%	100%

4.3.3. NeuCube

In NeuCube, raw data samples are fed into a dynamic SNN. One channel of an input sample was shown in Figure 2(a). Table 4 shows network parameters used by NeuCube. The model is established with 45 input neurons, 50 hidden neurons and output neurons (the number of samples). Due to the dynamic structure, the overall area overhead of NeuCube SNN is about $4.655\times10^{-3}\,\mathbf{mm}^2$ that is calculated according to neuronal and synaptic hardware area estimation proposed in [37,38]. Results shows that overall classification accuracy of NeuCube SNN is 98.9% (as shown in Figure 7).

Table 4. NeuCube Model Parameter Setting

Parameter		**Description**	**Value**
STDP Rate		Defines the learning rate of the STDP learning	0.01
Firing threshold		Defines the threshold membrane potential beyond which the neuron fires a spike.	0.5
deSNN Classifier Parameters	Mod	The weight is calculated as a modulation factor (the variable mod) to the power of the order of the incoming spikes.	0.55-0.6
	Drift	Initial connection weights are further modified to reflect the following spikes, using a drift parameter.	0.015

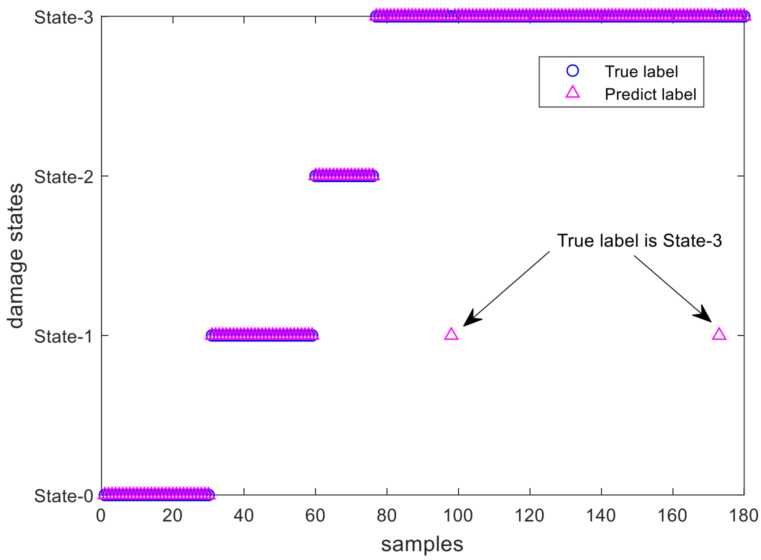


Figure 7. Classification result by using NeuCube (raw data)

Table 5 shows breakdown of performance accuracy for classification of damage states observed by NeuCube. Enough samples will contribute to higher probability of making correct decision about the damage states. As a comparison, mean samples are input into NeuCube with the same parameter setting above. The accuracy is not as stable as raw data input, as NeuCube is more sensitive to temporal raw data [39].

Table 5. Accuracy of each class

Damage state	Accuracy
State-0	100%
State-1	100%
State-2	100%
State-3	98.08%

4.3.4. Customized SNN

A customized fully connected SNN with LIF neurons and SpikeProp as learning algorithm is developed for the SHM classification based on previous work [40]. The three-layered fully connected SNN is designed and modelled in MATLAB. Table 6 shows network topology, size and hardware area of LIF based SNN model. Mean sensory samples are fed through 45 spiking input neurons to propagate spike towards 10 hidden neurons in order to generate 4 state output at 1 output neuron. The estimated hardware area of the SNN chip shown in Table 6 is calculated using [37,38].

Table 6. SNN setting and result (mean samples)

Network	Topology	Multiplier of synapses	Total neurons	Total synapses
SNN	[45:10:1]	10	56	460

Area of neurons	Area of synapses	Area overhead	Overall Accuracy	Number of iterations
5.04×10^{-4} **mm**^{2}	1.10×10^{-3} **mm**^{2}	1.61×10^{-3} **mm**^{2}	99.18%	2500
			99.46%	3000

Damage states are encoded with time of spike of output neuron (SNN output). Experimentation results shows the classification accuracy using mean samples input. Results shows in Table 7 that proposed customized SNN classifies structural damage with 99.18% accuracy for mean dataset. Moreover, the overall accuracy can be higher to 99.46% by increasing number of iterations, as compared to 98.9% NeuCube average accuracy for raw sensory input.

Table 7. Accuracy of each class

Damage state	SNN output	Accuracy	
State-0	16	100%	100%
State-1	18	95.67%	97%
State-2	20	100%	100%
State-3	22	99.8%	99.9%
Overall accuracy		99.18%	99.46%

4.3.5. Discussions

A summary of results using K-means, ANN and SNN in SHM applications, is shown in Table 8. ANN used raw data and feature samples as input, and there is little difference in classification accuracy. The final decision making can be the same within a certain confidence interval. Thus, if ANN combines the feature extraction into the learning process, it improves the computing speed, and also reduces the hardware consumption. The structural damage occurrence detection can be assessed as health (State-0) and damage (State-1, State-2 & State-3), then the sensitivity (true positive rate) and specificity (true negative rate) of three typical methods can be obtained with the input of raw data samples, as shown in Table 9. Compared with other two algorithms, SNN can accurately determine whether the structure is healthy. Meanwhile, the hardware area consumption of SNN is much less than ANN, the classification accuracy has a little difference of 0.9%, and the sensitivity and specificity are higher. In summary, the proposed method based on SNNs apparently achieves a good trade-off between classification, reliability, and hardware resource consumption.

Table 8. Performance comparison of three methods in SHM application

Method	Classification accuracy		Technology	Hardware area
	Raw data	Feature		
K-means	80%	100%	TSMC 90nm	1.23 **mm**^{2}~3.46 **mm**^{2}
ANN	99.8%	100%	CMOS 45nm	1.347 **mm**^{2} (neurons only)
SNN	98.9%	99.46%	CMOS 90nm	4.655×10^{-3}**mm**^{2} (NeuCube)
				1.61×10^{-3}**mm**^{2} (Customized SNN)

Table 9. Sensitivity and specificity comparison of three methods

Method	Sensitivity	Specificity
K-means	92.97%	73.87%
ANN	99.94%	99.15%
SNN	100%	100%

5. Conclusions

The structural health state detection in this study involves the feature extraction from periodically observation measurements of a structure, where these features are analysed to determine the current health state of the structure. Based on the detected states, appropriate repair and strengthening of structures can keep the structure operational and longeval. Through the analysis of ZCR, Mean and Variance of the raw sensor data, it is found by experiments that mean value is more sensitive to the structure state. Therefore, mean values and raw data were used as inputs, and several classification methods, including K-means, conventional ANN and SNN, were used to detect the health state of the structure. Analysis and comparison results show that the SNN algorithm proposed in this study has advantages including (a). High classification accuracy can be obtained by directly using the raw data as input without manual feature extraction; (b). The small part of misclassification (1.92%) only exists in State-3, where the output health states can be clearly distinguished; (c). The hardware area of SNN is lower compared to ANN or K-means. In summary, the proposed SNN hardware solution for SHM has a stronger survivability and reliability than conventional approaches. Further work will further optimize the SNN for SHM systems from two aspects including a). to develop multi-layer (deep) SNNs to improve the accuracy, and b). to further analyze the sensor data to enhance the system functionalities, such as reporting the location of damage or life forecast of the structure.

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